Journal of the Association for Information Systems (2019) **20**(7), 953-985
doi: 10.17705/1jais.00559

RESEARCH ARTICLE

ISSN 1536-9323

The Impact of Goal-Congruent Feature Additions on Core IS Feature Use: When More Is Less and Less Is More

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Abstract

This research investigates the impact of feature additions on the use of an information system's (IS) existing core features. Based on prior work in marketing and IS, we hypothesize conflicting effects on the usage of the system as a whole and the IS core due to the goal congruence of the two feature sets. In three consecutive empirical studies, we consider the example of a utilitarian consumer IS in the form of a mobile insurance app with additional weather-related functionality. The statistical results indicate that the goal-congruent feature addition exerts a positive influence on system use, whereas the impact on core IS use is negative. More specifically, we show that the latter effect can be explained by changes in the users' perceptions of the usefulness and ease of use of the core features. From a theoretical perspective, our work goes beyond the predominant system view of technology acceptance and use by employing a more fine-grained, feature-oriented level of investigation, which opens several avenues for further research regarding the relationships between information systems and the features they comprise. From a managerial perspective, the results help to characterize the detrimental effects that feature additions may have on IS usage. These consequences become particularly relevant when revenue, cost savings, or other benefits on the part of IS operators are linked only to a subset of the entire IS functionality, as in the case of certain web portals or mobile apps.

Keywords: IS Features, Goal Congruence, Convergent Products, Technology Acceptance, IS Use.

France Bélanger was the accepting senior editor. This research article was submitted on May 13, 2016 and went through five revisions.

1 Introduction

Over the past 20 years, the practice of developing and deploying information systems (IS) has undergone many fundamental changes. One example, among others, includes the proliferation of agile methods in software engineering (Fowler & Highsmith, 2001). In contrast to classic linear-sequential approaches to systems development, agile approaches are characterized by several shorter development cycles surrounding the creation of one or more IS features in terms of small functional units (O'hEocha & Conboy, 2010). A closely related paradigm shift has taken place in connection with "continuous deployment" (Humble & Farley, 2010), which provides the basis for faster, fully automatic release cycles driven by the completion of new features. A similar trend can also be observed in the optimization of web-based services (e.g., Facebook and Google) using randomized field experiments in the form of the very popular A/B testing (Kohavi, 2015). New features that exhibit a significant positive influence on user behavior are then rolled out across the entire user base, resulting in a mode of "perpetual development" (Feitelson, 2012), with the software being developed indefinitely.

A common denominator of all these developments is the view of the IS as an artifact in constant flux, with features continuously being added or enhanced. The underlying hopes and expectations on the part of practitioners are varied and include higher product quality, shorter time-to-market, and increased flexibility (Rigby, Sutherland, & Takeuchi, 2016). However, the ability to dynamically and iteratively change the set of features of an artifact also entails the challenge of selecting and prioritizing the right features that maximize the resulting value for users and companies (Daneva et al., 2013). This challenge, in turn, corresponds to the general issue of evaluating features when designing new products, a topic that has been discussed in the marketing literature for decades. Unfortunately, several studies indicate that the impacts of seemingly valuable feature additions are not always as positive as initially expected. Among other issues, feature additions can increase the perceived complexity of products, which counteracts the perceived usefulness (Thompson, Hamilton, & Rust, 2005). In some cases, depending on the type of existing core functions, the effect of a newly introduced feature may be associated with decreasing marginal utility. For example, research has demonstrated that the added value of a feature is perceived differently when it is added to a qualitatively inferior versus a qualitatively superior product (Nowlis & Simonson, 1996). In addition, the increase in utility can be lower than expected if new features are "goal-congruent"—i.e., if they share similar consumption goals with the base product (Gill, 2008; Gill & Lei, 2009).

The objective of the present study is to transfer and extend the findings from prior research on the role of goal congruence to an IS context, thus going beyond the predominant black box view of the information technology (IT) artifact. In contrast to marketing, only a few IS-related studies to date have considered the concept of features (Benlian, 2015; Jasperson, Carter, & Zmud, 2005), which brings the risk of overlooking important feature-specific effects that may remain invisible at the aggregated system level. As an example of such an effect, we investigate the impact of goal-congruent feature additions on the use of the existing core functionality of an IT artifact. Although both functional additions and goal congruence have been the subject of other studies, little is known about whether and why newly introduced features may have a negative impact on the existing product base. To explain these causal relationships with regard to IS features, we combine findings from marketing research with technology acceptance and use theory from IS. The research contribution that we make is twofold. First, we provide empirical evidence for the existence of opposing influences of feature additions on the acceptance and use of (1) the system as a whole and (2) its core functionality. Second, to explain this phenomenon, we demonstrate the applicability of existing models of IS acceptance at the feature level.

To this end, we present three consecutive empirical studies that consider the example of a consumer IS in the form of a mobile insurance app, which is extended by a weather forecast feature. We follow a directed program of experiments, as depicted in Figure 1, that aims to "systematically investigate over many experiments the explanatory variables that may account for an effect, gradually refining generalizations" (Shadish, Cook, & Campbell, 2002). In the first study, we investigate the suspected phenomenon by using a predictive model of app usage behavior and a quasi-experimental study design in the field. In a subsequent scenario-based survey experiment under laboratory conditions, we further isolate the observed effects and illustrate the connection between the introduction of a new goal-congruent feature and the intention to use existing core features. In a third study, considering insights from technology acceptance and use research, we test an explanatory model of the underlying mental decision-making process, which ultimately leads to a reduced intention to use the core features. Compared to using a single study, relying on multiple studies offers the advantage of greater control over which aspects are examined from experiment to experiment. The use of different research methods can also help to counterbalance the strengths and weaknesses of particular methods (Scandura & Williams 2000). The combination of the field and laboratory research we have chosen is typical for multimethod research design, which has become increasingly popular in management disciplines such as marketing (Simester 2017). For examples from both marketing and IS, we refer the reader to the studies by Schumann, von Wangenheim, & Groene (2014) and Hildebrand, Häubl, Herrmann, & Landwehr (2013).

The remainder of the paper is organized as follows. In the next section, we provide an overview of the theoretical foundations of our work in IS and marketing. In sections three through five, we present the three empirical studies, including hypothesis development, data collection, and the results of the statistical tests. In section six, we discuss our findings, implications, limitations, and areas for future research, and section seven concludes the paper.

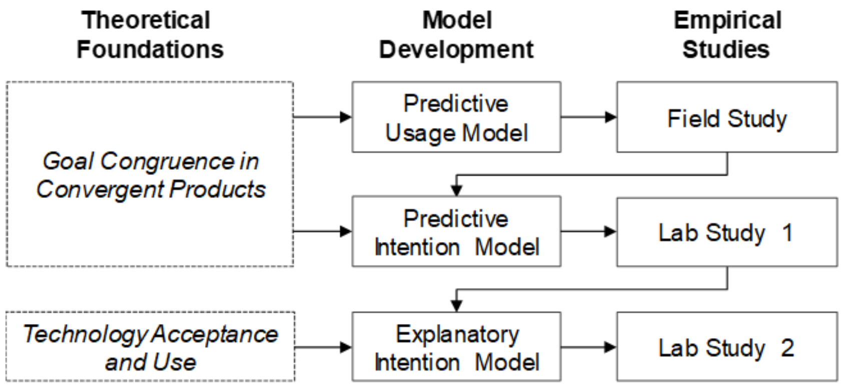

Figure 1. Multistudy Setup

2 Theoretical Background

2.1 Technology Acceptance and Use

The acceptance and use of IT artifacts are prominent and fruitful research issues in the IS discipline. The objective of this stream of scientific inquiry is to identify the factors that exert a direct or indirect effect on system use and to thus explain the observed variance in usage behavior among technologies. The views of scholars in this area have been profoundly shaped by the seminal work of Davis, Bagozzi, & Warshaw (1989) and their technology acceptance model (TAM). The TAM is based on Fishbein & Ajzen's (1975) theory of reasoned action (TRA), which describes human behavior as the consequence of attitudes (i.e., beliefs about the outcome of the behavior) and subjective norms (i.e., the influence of one's social environment). The TRA posits that attitudes and subjective norms are the key factors in the formation of behavioral intentions, which ultimately lead to actual behavior. Davis and his co-authors aimed to demonstrate that the logic of the TRA can be successfully transferred to the context of IS use. The TAM both simplifies and extends the TRA by attributing an individual's attitudes and system usage to two specific beliefs: (1) perceived ease of use (PEOU), and (2) perceived usefulness (PU). The model assumes that the influence of system design characteristics on usage is fully mediated by these beliefs (Davis, 1993).

Since its publication, the validity and generalizability of the TAM have been demonstrated for diverse fields of application, types of IT artifacts, organizations, cultures and geographical regions (King & He, 2006; Venkatesh & Bala, 2008). Some researchers have simply replicated the original TAM, whereas others have proposed modifications to further increase its explanatory power. These modifications can be grouped into three categories (Wixom & Todd, 2005). First, factors from related models, such as subjective norms, perceived behavioral control, and self-efficacy, have been added as antecedents to the *intention to use* (ITU) a system. Another approach has been to introduce further belief factors beyond PEOU and PU, including factors from the technology diffusion literature that follow the work of Rogers (1995), such as compatibility, trialability, and observability (Jeyaraj, Rottman, & Lacity, 2006). A third group of TAM extensions has examined external variables, including the abovementioned system design characteristics and, for example, personality traits and demographics.

In an attempt to integrate the various results of the research related to IS acceptance and usage behavior into a cohesive general model, some authors have proposed extended definitions of the original TAM. TAM2, developed by Venkatesh and Davis (2000), includes five additional factors that explain PU in terms of social influence and cognitive instrumental processes, in addition to two moderating factors (voluntariness and experience). TAM3, by Venkatesh and Bala (2008), sets the focus on the determinants of PEOU and integrates TAM2 with six factors identified by Venkatesh (2000). Another evolutionary path in the advancement of this research stream was established by Venkatesh, Morris, Davis, & Davis (2003), with their "unified theory of acceptance and use of technology" (UTAUT). In contrast to TAM2/3, the UTAUT proposes a completely newly formulated theoretical model. Based on an empirical comparison of eight existing models, including the TAM, these authors define four key determinants of a user's behavioral intention and usage behavior in addition to four moderating factors.

A noteworthy extension of the scope of the technology acceptance research has been made by applying the TAM and its successors to not only organizational settings but also to systems used by consumers. Here, the main difference from information systems within the firm is that technology use by consumers is not mandatory and cannot be explained by the usefulness of the corresponding systems (e.g., computer games) alone. In line with the consumer behavior literature that distinguishes between utilitarian and hedonic products (Hirschman & Holbrook, 1982), IS researchers have therefore begun to investigate the role of perceived enjoyment (PE), defined as "the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated" (Davis, Bagozzi, & Warshaw, 1992). This line of research includes works by van der Heijden (2004) and Thong, Hong, & Tam (2006), which demonstrate significant influences exerted by PE. Consequently, the factor has ultimately found its way into the unified models of acceptance and use. In the case of the TAM3, the model includes PE as a determinant of PEOU. The most recent version of the UTAUT by Venkatesh, Thong, & Xu (2012), again, has been formulated specifically to include factors that are important in consumer settings. The authors consider not only enjoyment (conceptualized as "hedonic motivation") but also the cost/price ratio of the technology and of the user's habits.

Despite its enormous popularity, research based on the TAM has often been criticized not only for the typical limitations of some studies, such as the use of self-reported data on system usage (Lee, Kozar, & Larsen, 2003) but also for a number of reasons that apply to the research stream as a whole. In addition to shortcomings regarding the assumed intention-behavior linkage (Bagozzi, 2007) and the lack of model parsimony (Straub & Burton-Jones, 2007), another fundamental critique focuses on the practical relevance of TAM research (Benbasat & Barki, 2007; Grover & Lyytinen, 2015). Although the corresponding studies have undoubtedly contributed to our theoretical understanding of how and why systems are accepted and used, the number of nontrivial actionable insights for practitioners that could be derived from this body of knowledge is described as rather poor in several scholars' commentaries. Some critics attribute this weakness to the absence of the IT artifact in the respective models (Benbasat & Zmud, 2003; Orlikowski & Iacono, 2001), whereas others lament IS researchers' habit of considering IT artifacts as immutable black boxes (Wixom & Todd, 2005). In the latter case, a system's characteristics are considered only in a more holistic manner rather than as the result of several specific design and implementation choices regarding coherent functional building blocks (i.e., the features of a system), which together shape the profile of the system as a whole. Similarly, in the clear majority of studies, technology use is examined on a system level, whereas investigations of individual features or feature sets are still very scarce (Benlian, 2015; Jasperson et al., 2005).

2.2 Product Evaluation and the Impact of New Features

In contrast to IS research, marketing research has long considered the relationships between features and consumer behavior. Here, the main research objective has been to understand how different combinations of product features influence the consumer's evaluation of the product. At least since Lancaster's (1966) work, researchers have recognized that consumers choose more between the characteristics of goods than between the goods themselves. The resulting theoretical models describe the preferences of consumers in the form of an additive utility function, which assumes that a higher number of positively evaluated features increases the benefits for the consumer. The logic of this purely rational view of consumer behavior is reflected in many current market research methods, such as conjoint analysis and discrete choice analysis. Consequently, companies tend to regard every new feature as a means of increasing their products' market share, relative to products without that feature (Brown & Carpenter, 2000; Rust, Thompson, & Hamilton, 2006).

However, newer research suggests that the traditional view of the product evaluation process and the role of features for that process cannot be generalized, in practice, to all settings (Meyer, Zhao, & Han, 2008). For example, Nowlis & Simonson (1996) investigate factors that moderate the impact of a new feature on brand choice. Building on the principles of multi-attributes with respect to diminishing sensitivity and performance uncertainty, they demonstrate that a new feature adds greater value and increases the choice share of a brand more when the brand has relatively inferior existing features, is associated with lower (perceived) quality, has a higher price, or is both high-priced and high-quality. Similarly, Mukherjee & Hoyer (2001) demonstrate that the positive effect of novel features occurs in products with low complexity, whereas added features of highly complex products can be detrimental to the product evaluation. Mukherjee and Hoyer conclude that in the latter case, the consumer's response to new features is overshadowed by the higher cognitive effort associated with the necessary knowledge acquisition related to product complexity. Thompson et al. (2005) introduce the term "feature fatigue" to describe the phenomenon of products receiving different evaluations before and after use. The authors argue that the number of features has an impact on both the perceived capability of a product and its perceived usability. Data from three empirical studies indicate that before using a product, consumers put more weight on a product's capabilities than on its usability. However, consumer preferences change over time, and user-friendliness becomes a key factor in consumer satisfaction during use. As a result, perceived product benefits can ultimately decrease significantly if consumers are frustrated or dissatisfied with the number of features.

In recent years, the importance of a more differentiated view of features has further increased as a consequence of the convergence of industries, resulting in a large number of so-called "convergent products" (Gill, 2008; Han, Chung, & Sohn, 2009; Lee, Lee, & Garrett, 2013), among other outcomes. Beyond conventional functional extensions or product bundles, convergent products integrate the functionality of different product categories into a coherent new product (e.g., Internet-connected cars, wearable electronics, and smart refrigerators). The most extreme example is most likely the development of smartphones, which has turned mobile telephones with predefined functionality into the digital equivalent of a Swiss Army knife. Convergence affects various industries, including the semiconductor, telecommunications, entertainment, consumer electronics and computer industries (Gill, 2008; Yoffie, 1996). Against the backdrop of disintegrating industry boundaries and shortening product lifecycles, it seems obvious for many companies to supplement an existing base product with features from another product category to maintain high profit margins and differentiate themselves from competitors in the same market segment. The economic rationale assumes that the perceived value of a product corresponds to the sum value of its features.

In an empirical study, using the example of two base products (a PDA and an MP3 player) and eight different functional extensions, Gill (2008) examines the role of the following two factors in the consumers' assessment of convergent products: (1) the goal congruence between the added functionality and the base product, and (2) the utilitarian or hedonic nature of both functionalities in the evaluation of the resulting convergent products. Following Huffman & Houston (1993), goals are defined as abstract benefits that consumers seek in specific consumption situations, and consumers can obtain utilitarian or hedonic value by achieving these goals. Goal congruence implies that consumers seek similar benefits and value from both the added functionality and the base product (Gill, 2008). A necessary precondition for goal congruence between features is that the features support the achievement of goals from the same category (i.e., utilitarian or hedonic). When the two features belong to the same category, the actual congruence can vary in strength. Goal congruence is hence a nondichotomous property, the degree of which depends on the similarity of the respective goals.

The empirical results by Gill (2008) indicate the existence of asymmetric additive effects, which can differ fundamentally depending on the type of base product and the added feature. For instance, it was found that utilitarian features that are added to a utilitarian (i.e., goal-congruent) base product are subject to diminishing utility. In contrast, the same convergent product benefits much more from the addition of hedonic (i.e., not goal-congruent) features, which are perceived to enhance the base. Gill (2008) also considers the role of prior ownership as a moderating factor. The tests indicate that ownership effects occur only in products with a hedonic base product, not in those with a utilitarian base.

3 Predictive Usage Model

3.1 Hypotheses Development

Both research strands reviewed in the previous section share the same theoretical rationale, with capability/PU and complexity/PEOU being major determinants of consumer behavior. However, both also share limitations, which we aim to address in the present study. On the one hand, marketing studies consider product evaluation in terms of perceived utility or willingness to pay. Here, the variable of interest is the perceived incremental value of the entire product after further features are added; however, prior research has not considered the impact that goal-congruent feature additions may have on usage behavior, in general, and on usage of the former product base, in particular. IS research, on the other hand, has a long tradition of investigating intention to use and actual use as the main dependent variables, but it does so almost exclusively on the system level, with feature use typically being neglected. Hence, the following question arises: At the system and feature levels, what is the impact of new goal-congruent features on the use of already existing IS features?

Based on the findings from prior research, we expect a detrimental impact of a goal-congruent feature addition, reflected by a simultaneous increase in total system use and a decrease in core feature use (i.e., features already available before the feature addition will be used less after the feature addition). However, whereas the difference in total use may be expected from the literature, the negative influence on core feature use needs further theoretical elaboration. Although the study by Gill (2008) suggests the existence of this latter counterintuitive effect, to date, it has been neither tested nor explained. Accordingly, we start by formulating two hypotheses for both effects, which we aim to confirm in an empirical study. Our research objective in this first step is to provide evidence for the described phenomenon, which is reflected by an impact on actual use behavior. Taken together, both hypotheses form a predictive usage model (see Figure 2)—that is, a model that predicts outcomes from one or more factors without explaining the underlying causal connections in detail (Gregor, 2006).

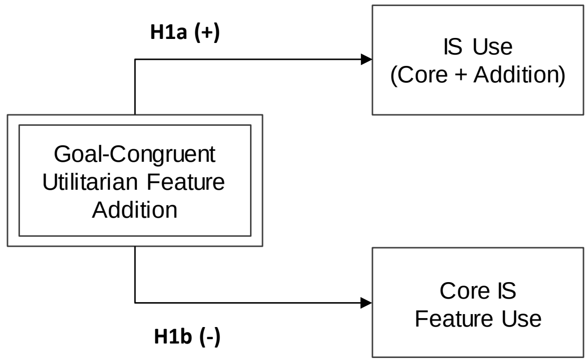

Figure 2. Predictive Usage Model

The concept of goal congruence and its role in the context of adding new features to a product has its theoretical roots in assimilation/contrast effects, a psychological phenomenon observed in the judgment of new stimuli in the assessment of both people and objects (Herr, Sherman, & Fazio, 1983; Schwarz & Bless, 1992). It has been shown that a new stimulus can be either assimilated into or contrasted from a context, depending on factors such as the degree of feature overlap between the context and the new stimulus. In connection with the development of new products, Meyers-Levy & Tybout (1989) find that the addition of slightly incongruent features is preferred to congruent ones, with feature incongruence being defined in terms of the perceived distance between the feature and the product. Similarly, Ziamou & Ratneshwar (2003) analyze assimilation/contrast effects when a new functionality is added to a product and compared with another existing functionality.

Gill (2008) proposes that the balance between assimilation and contrast effects depends on the goal congruence between the new feature and the base product. When a congruent, utilitarian (hedonic) functionality is added to a utilitarian (hedonic) base product, the overlap in the underlying goals leads to the assimilation of the new functionality into the existing base. Assimilation influences how consumers perceive the value (or utility) associated with the new feature and the base product. The additive effect ultimately manifests itself in a decreasing marginal utility of the congruent functionalities—in other words, the incremental value of new features declines along with the total value of the product (Nowlis & Simonson, 1996). The perceived value of the product including the newly added feature is thus subadditive.

We hypothesize that the described effects can also be observed in the context of IS use. This assumption is based on the known relationship between the users' positive evaluation of system characteristics and subsequent use (Venkatesh et al., 2003). We therefore assume that a change in the perceived value of an IT artifact by adding features is also reflected in later use behavior. We investigate this phenomenon on two levels. On the one hand, we expect an increase in the use of the overall system as a consequence of its extended functionality. In the context of goal congruence between features, a decreasing marginal utility is foreseeable, but nevertheless, the overall utility after the addition of features is higher than before, and, therefore, the effect on actual usage should be positive. On the other hand, we expect that the use of the existing core features of the IT artifact will decrease. The rationale behind this second assumption is that the concept of assimilation does not describe a unidirectional influence of one feature group on another but rather an effect that affects both sets of features simultaneously. Regarding the features of the original IS, we expect that these will be used less after the addition of the goal-congruent features. The study by Gill (2008) indicates that assimilation is strongest in the case of utilitarian features. Hence, in the following hypotheses, we focus on a utilitarian system to which further utilitarian, goal-congruent features are added. We formulate the two hypotheses regarding the impact of goal-congruent feature additions at the system and feature level as follows:

H1a: Adding a goal-congruent utilitarian feature to a utilitarian IS will have a positive effect on total IS use.

H1b: Adding a goal-congruent utilitarian feature to a utilitarian IS will have a negative effect on core IS feature use.

3.2 IT Artifact

To observe the real-world behavior of IS users and to test our hypotheses in the field, we cooperated with a property insurance company that offers a smartphone app for its customers. The expected benefits of the app from the insurer's perspective were twofold. First, the company hoped to differentiate itself from competitors by creating added value for its customers, thus strengthening customer relations beyond traditional forms of insurance marketing. Second, to save costs, the company wanted to partially automate labor-intensive workflows associated with emergency assistance and insurance claim processing. As such, the app allows users to do the following: call a central emergency hotline or use official emergency numbers to call the police, the ambulance, or the fire department; contact a local insurance agency for help or specialists for legal advice; and electronically submit the details of an insurance claim.

The first release of the app (R1) became available in 2010, and the software was further improved in a second release (R2) one year later. In an attempt to increase the popularity and usage frequency of the app, an additional feature, which extended capabilities beyond a pure emergency and claims context by providing weather information and offering a warning service for severe weather conditions, was integrated into the app (R3) in June 2012. Table 1 presents an overview of the features provided by the app in the two latter releases. In the context of our study, the IS core features correspond to the original functionality of the earlier release, R2, of the app, whereas the weather-related functionality was treated accordingly as the feature addition in R3 (cf. Appendix B for exemplary screenshots).

There are three reasons why the weather feature qualifies as an appropriate representation of a feature addition in the context of our study. First, the core app and the new weather functionality are independent features—that is, they do not build on each other and could be implemented as separate apps. Second, both feature sets are utilitarian in nature, which, based on Gill (2008), is a prerequisite for a pronounced subadditive effect. Furthermore, while the features do not support the achievement of the same specific goal, they can be assumed to show a considerable degree of goal congruence. The purpose of the core features is to digitally provide the services of a property insurance company. The weather feature, in turn, includes alerts in case of severe weather conditions, and is directly aimed at enabling the user to proactively protect his or her property from damage (e.g., park the car in a covered area in case hail is forecast). Thus, however different they seem to be at first glance, both types of features pursue similar goals of loss protection.

3.3 Pretest

To ensure that our assumptions about the utilitarian nature of the app's different features and their goal congruence hold in this particular field of application, we first conducted a pretest with 106 participants. The corresponding online research panel was recruited via Amazon Mechanical Turk (MTurk), and participants received a small monetary compensation for their efforts. MTurk is an online marketplace for crowdsourcing work tasks (Schulze, Krug, & Schader, 2012). The use of MTurk in behavioral and IS research has increased rapidly in recent years because it enables fast and inexpensive sampling (Behrend, Sharek, Meade, & Wiebe, 2011; Goodman, Cryder, & Cheema, 2013). In addition, the MTurk subjects' demographics are more diverse than those of traditional subjects (e.g., students), and the results are comparable with those of lab experiments (Horton, Rand, & Zeckhauser, 2011; Mason & Suri, 2012; Paolacci, Chandler, & Ipeirotis, 2010). However, it is also known that MTurk data can threaten the validity of findings (Zhu, Barnes-Farrell, & Dalal, 2015).

Table 1. Releases, Features, and Functionality of the Insurance App

Feature	Functionality	R2	R3
Core	• My agency: find and contact the insurance agency • Insurance emergency call: fast and easy access to the insurance company's emergency line • Insurance legal help call: fast and easy access to the insurance company's legal helpline • Public emergency call: fast and easy access to police, ambulance, or fire department emergency hotlines • Claims management: submit and manage claims • Claims sketches: replay popular TV insurance ads	X	X
Weather	• Meteorology alarm: warning map with severe weather conditions • Warning details: detailed information on specific warnings • Warning settings: subscription to push warnings • Weather forecast: precipitation forecast		X

More specifically, recent evidence suggests that "researchers should avoid using MTurk when participant anonymity creates a strong possibility for dishonest responses or when the entire study would be made invalid if the participants' self-reported identities are false" (Jia, Reich, & Jia, 2016). Since none of these conditions apply in the context of our study, MTurk was leveraged in accordance with the Steelman (Steelman, Hammer, & Limayem, 2015) guidelines (cf. Appendix C), and participants were shown screenshots (cf. Appendix B) with corresponding explanations of the app. Initially, screenshots of the core features, which were explicitly introduced and labeled "base features" in the survey, were shown. Then, screenshots of the weather features (feature addition), which were again clearly introduced and labeled "weather features," were shown. Finally, participants were asked to provide an evaluation of the app (cf. Appendix A).

Following Gill (2008), the hedonic value and utilitarian value of the core and weather features were measured on the basis of Voss, Spangenberg, & Grohmann (2003), with three items ("unhelpful/helpful", "impractical/practical," "not functional/functional") for the utilitarian value (averaged to one measure, with $\alpha = 0.95$ for core features and $\alpha = 0.95$ for added features) and three others ("disgusting/enjoyable," "dull/exciting," "not thrilling/thrilling") for the hedonic value (averaged to one measure; $\alpha = 0.86$ for core features; $\alpha = 0.89$ for added features): the scales ranged from 1 to 7. Goal congruence was measured using the two items from Gill (2008), based on Martin & Stewart (2001): (1) "How similar is the goal associated with base features and weather features?" and (2) "How similar is the reason for using base features and weather features?" The two items thus reflect the nondichotomous nature of goal congruence between features. Both scales ranged from 1 ("not at all similar") to 7 ("very similar") and were averaged to yield one measure ($\alpha = 0.78$). The results indicate that the core features were indeed associated with relatively more utilitarian than hedonic values (6.19 versus 4.43; $t(105) = 14.71$, $p < 0.001$). The weather features were also associated with relatively more utilitarian than hedonic values (6.16 versus 4.78; $t(105) = 12.69$, $p < 0.001$). Furthermore, a one-sample t-test was run to determine whether the score of 4.79 was different from neutral, which was defined as a score of 4. The result shows that the core and added features were perceived as goal-congruent (4.79 versus 4; $t(105) = 6.50$, $p < 0.001$). Compared to the corresponding setting (utilitarian base and utilitarian addition) of Gill (2008), our feature set is characterized by a slightly higher goal-congruence score (4.79 versus 4.76).

3.4 Measurement Instruments and Data Collection

We continued with the main study in the form of a quasi-experiment (Shadish et al., 2002) based on usage data from real app users. Here, usage of the app was measured per device on a screen-by-screen basis—i.e., by the number of times a user opened a particular screen of the application. To assess the effect of the feature addition on core feature usage, the number of screen views within both the core and the entire application was analyzed. We evaluated the data provided by the insurance company from a total of 6,665 devices that were selected based on three basic criteria from the entirety of app installations. First, on all devices, the app had been used for the first time between July 1, 2011, and September 30, 2012. Second, at least five screens of the app had been viewed on each device. Third, the devices were not used by insurance employees (e.g., for customer presentations) or developers of the app (e.g., for security tests). In addition, only the R3 devices (devices with the newer version released in 2012 that included the weather features) that had not previously used R2 (devices with earlier app version released in 2011 without weather features) were considered. Anonymous but unique device IDs allowed us to determine devices that were updated from R2 to R3. As such, we were able to review the first three months of app usage (90 days) on each device, including details about which screens users had viewed within the application. On 2,208 devices, the R2 release was installed, whereas on the other 4,457 devices, the R3 release was installed. The total usage of the app included screen views of (1) the core features, (2) the weather features, and (3) other features, including the home screen and setting screen views, which were counted as neither core nor weather feature use.

3.5 Results

A mixed-effects repeated measures analysis was applied to analyze the data. In contrast to a repeated-measures ANOVA, the mixed-effects repeated measures analysis assumes neither sphericity nor compound symmetry, and the parameter estimates are not affected by nonnormality (Gelman & Hill, 2007). The model specification is given by the following formula:

$$y_{im} = c + \beta_{r2}T_{r2\_im} + \beta_{m2}T_{m2\_im} + \beta_{m3}T_{m3\_im} + \beta_{r2m2}T_{r2m2\_im} + \beta_{r2m3}T_{r2m3\_im} + \varepsilon_{im} \quad (1)$$

where y_{im} denotes the app usage in terms of the number of screen views by user i in month m. The constant c equals the use of R3 in the first month. The dummy variable T_{r2_im} indicates whether user i is using R2 ($T_{r2\_im} = 1$). Two further dummy variables, T_{m2_im} and T_{m3_im}, represent the time dimension, with $T_{m2\_im} = 1$ in Month 2 and $T_{m2\_im} = 1$ in Month 3. The β_{r2m2} and β_{r2m3}

coefficients capture the two potential interaction effects between time (i.e., month) and release. T_{r2m2_im} (T_{r2m3_im}), for example, takes the value of 1 if user *i* is using R2 and the corresponding screen views occur in the second (third) month. We conducted the analysis for both total app usage and core feature usage. The resulting parameter estimates are summarized in Table 2.

Concerning total app usage, the estimation resulted in a significant model with Wald $\chi^2(5) = 13307.56$, $p < 0.001$. R3 users were predicted to view a total of 26.57 screens in the first month (constant). R2 users were predicted to view 6.75 screens fewer than R3 users over all three months (significant main effect). For R2 and R3 users, screen views were estimated to drop by 23.41 in the second month (compared to the first month) and by 24.93 in the third month (compared to the first month). Finally, the model predicted a less severe drop in usage for R2 users. In comparison to R3 users, R2 users viewed 5.67 more screens in the second month and 6.49 more screens in the third month. To confirm significant usage differences between the two groups over time, we calculated contrasts. The results for total use indicate that R2 users viewed significantly fewer screens in the app as a whole than R3 users did in Months 1 and 2. In the first month, R2 users viewed an average of $M = 19.82$ ($SD = 17.05$) screens, which is significantly less than the average of R3 users ($M = 26.57$, $SD = 23.79$); $z = -18.72$, $p < 0.001$. Similarly, R2 users viewed significantly fewer screens within the overall app in Month 2 ($M = 2.08$, $SD = 6.81$) than R3 users did ($M = 3.16$, $SD = 8.99$); $z = -2.99$, $p < 0.001$. However, in the third month, no significant difference could be found between R2 users ($M = 1.38$, $SD = 4.94$) and R3 users ($M = 1.64$, $SD = 5.82$); $z = -0.7$, $p = 0.244$.

We then estimated a second model with core feature views as the dependent variable that is significant with Wald $\chi^2(5) = 6242.73$, $p < 0.001$. According to the estimation results, R3 users were predicted to view 6.71 core screens in the first month (constant). R2 users were predicted to view 2.67 core screens more than R3 users did over all three months (significant main effect). However, for R2 and R3 users, usage was expected to decrease by 5.91 in the second month (compared to the first month) and by 6.13 in the third month (compared to the first month). Finally, the model predicts an additional drop in usage for R2 users. In comparison to R3 users, R2 users were expected to reduce their usage by 2.14 views in the second month and 2.37 views in the third month. To gain a deeper understanding of core feature usage by the two groups over time, we calculated contrasts. The results show that in the first month, users of R2 used significantly more of the app's core functionality ($M = 9.16$, $SD = 10.87$) than did the R3 users ($M = 6.49$, $SD = 8.76$); $z = 16.90$, $p < 0.001$. This difference also remains significant in the second and third months, albeit at declining significance levels. In the second month, R2 users made more use of the core features than did R3 users: R2 users viewed an average of $M = 1.11$ ($SD = 4.79$) core feature screens compared to R3 users, who viewed an average of $M = 0.58$ ($SD = 3.22$); $z = 3.34$, $p < 0.001$. The same could be observed in the third month, in which R2 users ($M = 0.67$, $SD = 3.01$) made significantly more use of the core features than R3 users did ($M = 0.37$, $SD = 2.01$); $z = 1.90$, $p < 0.05$.

Table 2. Repeated Measures Mixed Models

Variable	Total usage (core + addition)	Core feature usage
Constant	26.57*** (0.21)	6.71*** (0.14)
Release R2 (β_{r2})	-6.75*** (0.36)	2.67*** (0.16)
Month 2 (β_{m2})	-23.41*** (0.28)	-5.91*** (0.12)
3 (β_{m3})	-24.93*** (0.28)	-6.13*** (0.12)
Release x Month R2 x 2 (β_{r2m2})	5.67*** (0.48)	-2.14*** (0.22)
R2 x 3 (β_{r2m3})	6.49*** (0.48)	-2.37*** (0.22)
Notes: **standard errors in parentheses; *p < 0.05, **p < 0.01, and ***p < 0.001**		

In summary, the results of Study 1 support Hypothesis H1a—which posits that feature additions exert a positive effect on overall IS use—and H1b regarding the negative effect on core feature use. Both effects were found to decline over time because the total usage intensity of the app drops significantly. However, such a slump in app usage sometime after installation is a common phenomenon with free smartphone apps. Schonfeld (2009), for instance, reports that only 20% of users log into free apps on the day after the download and that less than 5% are still using them after 30 days. Nevertheless, the first study has some limitations that may be considered typical for investigations in the field. Since we analyzed real-world data from a publicly available app, self-selection effects cannot be excluded. Temporal effects may also have affected our results because the different releases of the application were not launched at the same point in time. Moreover, the app is accessible to the general public, which means that both customers and noncustomers of the insurance company may use it. Although it is possible that insured customers may exhibit a different usage pattern than noncustomers, the user type cannot be determined from our data set unless a claim is submitted through the application. It should be noted that we evaluated the data at the device level. However, although it is conceivable that multiple users may have used the app on the same device, the traditionally strong binding between users and their mobile devices renders this scenario somewhat unlikely.

4 Predictive Intention Model

4.1 Hypothesis Development

The first study provided initial empirical evidence of the existence of the previously only suspected impact of extending an IT artifact with goal-congruent usage features. However, although field research allows observation of the phenomena in a natural environment, it does not meet the same rigorous methodological requirements as laboratory experiments. Therefore, we cannot exclude with certainty that variances in the data are caused by unknown external variables. For this reason, under controlled conditions, we conducted a second study, the aim of which was to further isolate the previously identified effects and provide additional support for the internal validity of our causal inferences. Moreover, in a first step toward investigating the mental process that precedes actual usage behavior, we shifted our focus to the intention to use an IT artifact.

Following the same theoretical considerations as in the first study, we expected contradictory effects of a utilitarian, goal-congruent feature addition on the usage intentions at the system and feature level. We therefore modified our first research model by replacing the two dependent variables (see Figure 3). Furthermore, in this instance, our model does not yet make any more detailed assumptions about the underlying causalities. We formulate the corresponding hypotheses as follows:

H2a: Adding a goal-congruent utilitarian feature to a utilitarian IS core will have a positive effect on the intention to use the IS.

H2b: Adding a goal-congruent utilitarian feature to a utilitarian IS core will have a negative effect on the intention to use core IS features.

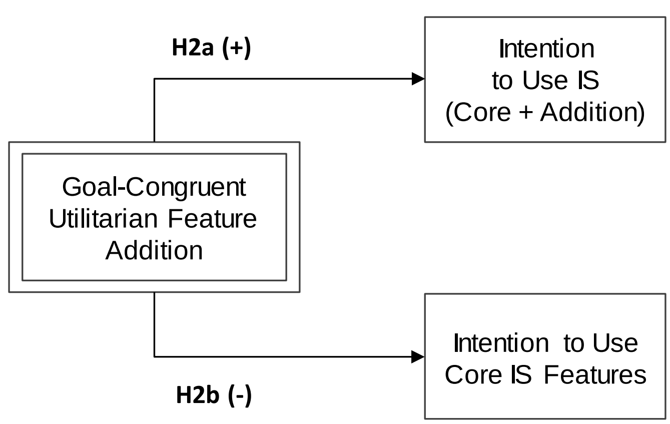

Figure 3. Predictive Intention Model

4.2 Measurement Instruments and Data Collection

Rather than testing H2a-b in one experiment, we chose to conduct two independent scenario-based survey experiments to ensure that responses concerning the core and total feature sets did not interfere. To investigate the effect of the goal-congruent feature addition on overall IS usage intentions (H2a) in a lab experiment, we collected data from two randomized groups of participants: Group A and Group B. Participants in Group A were shown screenshots (cf. Appendix B) of the core features (i.e., the R2 release of the app). Participants in Group B were presented with both the core features and the added weather-related features (i.e., the R3 release). Participants were then asked about their intentions to use the app. To validate the negative effects of goal-congruent feature addition on core IS usage intentions (H2b), in a second lab experiment, we collected data from two randomized groups of participants, Groups C and D. Again, participants in Group C were shown screenshots (cf. Appendix B) of the core features (i.e., the R2 release); participants in Group D viewed both the core features and the added weather-related features (i.e., the R3 release). In contrast to the first experiment, participants were then asked about their intentions to use the core features.

For both experiments, participants were recruited via Amazon MTurk and received a small monetary compensation. To ensure an adequate understanding of both the app and the requested assessments, we required participants to be located in the US and we included additional comprehension checks in the survey to validate that the participants had viewed and understood the screens and explanations. To ensure that pretest subjects did not participate in the experiments, we (1) noted that repeated participation would not be compensated, and (2) checked the anonymous worker IDs for repeated participation. In total, 623 participants took part in the survey and were randomly assigned to the experimental groups. Of these, 145 participants (23.2%) were excluded from the study because they either did not fully complete the survey (124) or made more than two errors in their answers (21) to the control questions. Hence, we collected a total of 478 valid responses.

Table 3 provides an overview of the demographic characteristics of the participants in the four experimental groups. It should be noted that 3.1% of the participants stated that they did not own a smartphone, so they would not currently be able to use the app. However, we decided to keep these people in the sample anyway, since purchasing a smartphone does not pose a substantial obstacle to developing an intention to use a mobile app and there is no reason to assume that the effects of feature addition are not present in the case of lower intentions. Furthermore, understanding the app's functionality does not require any personal experience beyond basic IT knowledge of how to use a smartphone.

The scales for the study were adapted from prior research (cf. Appendix A). The items for measuring usage intentions with regard to the entire app were adapted from Venkatesh et al. (2012). The scale reflects one of the primary goals of the insurance company: achieving a high usage frequency. Each of the items was measured on a 7-point Likert scale (1 = extremely unlikely, 7 = extremely likely), and the items were found to form a cohesive construct, with Cronbach's $\alpha = 0.97$. In contrast, the app's core features are utilitarian in nature and offer support in insurance-related situations (emergencies, losses, claims, and legal issues, for example) that do not occur on a regular basis. Hence, since a frequency-based operationalization of the construct seemed somewhat inappropriate, we chose a more generic operationalization (e.g., "feels comfortable to use," "would use," and "would recommend use") based on items adapted from Nicolaou & McKnight (2006), Liu, Marchewka, Lu, & Yu (2004), and Davis et al. (1989). Each of the items was measured on a 7-point Likert scale (1 = extremely unlikely, 7 = extremely likely), and they were found to form a cohesive construct, with Cronbach's $\alpha = 0.94$.

4.3 Results

Significant differences were found between the experimental groups in terms of the participants' intention to use the app and their intention to use the core features. Providing support for H2a, the average intention to use the app was significantly higher in Group A ($M = 4.569$, $SD = 1.1688$) than in Group B ($M = 3.397$, $SD = 1.736$); $t(231) = -5.215$, $p < 0.001$. In accordance with H2b, the average intention to use the app's core features was significantly lower in Group D ($M = 5.189$, $SD = 1.233$) than in Group C ($M = 5.667$, $SD = 1.364$); $t(245) = 2.769$, $p < 0.01$.

Taken together, the second study further corroborates the findings that we observed previously in the field. In contrast to the first study, the measurement was restricted to usage intentions. The collected data were therefore limited to the measurement of usage intentions. However, the more controlled environment allowed other influencing factors that may have offered alternative explanations for the phenomenon observed in the field to be disqualified. The fact that similar effects occurred in both the field and the lab hence provides strong support for Hypotheses H2a and H2b.

Table 3. Sample Characteristics

		Group A	Group B	Group C	Group D
Measurement		*Total usage (core + addition)*		*Core feature usage*	
Feature set		***R2***	***R3***	***R2***	***R3***
N		***116***	***116***	***142***	***104***
Age	Less than 25 years	31 (26.7%)	27 (23.3%)	41 (28.9%)	25 (24%)
	25-34 years	50 (43.1%)	51 (44%)	73 (51.4%)	58 (55.8%)
	35-44 years	17 (14.7%)	13 (11.2%)	16 (11.3%)	14 (13.5%)
	45-54 years	10 (8.6%)	17 (14.7%)	7 (4.9%)	4 (3.8%)
	55 years and older	8 (6.9%)	8 (6.9%)	5 (3.5%)	3 (2.9%)
Gen-der	Male	58 (50%)	69 (59.5%)	52 (36.6%)	37 (35.6%)
	Female	58 (50%)	47 (40.5%)	90 (63.4%)	67 (64.4%)
Monthly income	Less than $1,300	16 (13.8%)	22 (19%)	23 (16.2%)	21 (20.2%)
	$1,300-$2,600	24 (20.7%)	13 (11.2%)	19 (13.4%)	24 (23.1%)
	$2,600-$3,600	7 (6%)	15 (12.9%)	17 (12%)	5 (4.8%)
	$3,600-$5,000	5 (4.3%)	8 (6.9%)	4 (2.8%)	3 (2.9%)
	$5,000-$10,000	5 (4.3%)	7 (6%)	10 (7%)	18 (7.7%)
	More than $10,000	24 (20.7%)	21 (18.1%)	27 (19%)	17 (16.3%)
	No answer	35 (30.2%)	30 (25.9%)	42 (29.6%)	26 (25%)
Education	High school	14 (12.1%)	16 (13.8%)	31 (21.8%)	25 (24%)
	Technical degree	4 (3.4%)	6 (5.2%)	4 (2.8%)	2 (1.9%)
	1-3 years college	35 (30.2%)	34 (29.3%)	39 (27.5%)	26 (25%)
	Bachelor’s degree	52 (44.8%)	49 (42.2%)	51 (35.9%)	43 (41.3%)
	Graduate degree	10 (8.6%)	10 (8.6%)	17 (12%)	6 (5.8%)
	Other	1 (0.9%)	1 (0.9%)	0 (0%)	2 (1.9%)
Employment status	Employed	61 (52.6%)	68 (58.6%)	83 (58.5%)	61 (58.7%)
	Self-employed	21 (18.1%)	19 (16.4%)	25 (17.6%)	15 (14.4%)
	Student (high school)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Student (university)	16 (13.8%)	12 (10.3%)	19 (13.4%)	16 (15.4%)
	Unemployed	14 (12.1%)	12 (10.3%)	15 (10.6%)	11 (10.6%)
	Other	4 (3.4%)	5 (4.3%)	0 (0%)	1 (1%)
Smartphone	iPhone	55 (47.4%)	45 (38.8%)	52 (36.4%)	37 (34.9%)
	Samsung	35 (30.2%)	38 (32.8%)	41 (28.7%)	28 (26.4%)
	Nokia	1 (0.9%)	2 (1.7%)	6 (4.2%)	6 (5.7%)
	HTC	6 (5.2%)	7 (6%)	13 (9.1%)	11 (10.4%)
	Other	17 (14.7%)	25 (21.6%)	26 (18.2%)	19 (17.9%)
	No smartphone	2 (1.7%)	3 (2.6%)	5 (3.5%)	5 (4.7%)

5 Explanatory Intention Model

5.1 Hypotheses Development

After the effects of additional IS features were investigated in the field and in the laboratory, we used Study 3 to shed light on the causalities behind them. Since the observed positive effects on overall system use and usage intentions were to be expected against the backdrop of prior research, we concentrated on the second, and as yet unresolved effect, on the use of IS core features. For this purpose, we developed an explanatory model of the mental process that leads to the intention to use core IS features, which allowed us to reconstruct the influence of new goal-congruent features. Since the formation of behavioral intentions in the context of IS use has been the subject of an extensive body of literature, we utilized an established theory in the form of the TAM model. Through a series of mediating factors that make it an obvious candidate for investigating the effect of new features on these factors, the TAM explains the relationship between the system characteristics and the intention to use a system. The validity of the TAM model and its extensions at the system level have been confirmed in numerous studies. Our assumption is that the model can also explain the intention to use core IS features, since these features were equivalent to the overall system prior to the addition of new features. Accordingly, we formulated TAM-related hypotheses regarding the influence of new, goal-congruent features, with the intention to use the core IS features being the primary dependent variable. The resulting research model is illustrated in Figure 4.

Following the logic of TAM, we hypothesize that feature use is driven by the perceived usefulness and also by the perceived ease of use of IS features, with PEOU exerting a positive influence on PU (Davis, Bagozzi, & Warshaw, 1989). We also include perceived enjoyment as a third independent variable in our model. Prior research has demonstrated that the utilitarian/hedonic nature of an information system is an important boundary condition for the validity of the TAM (Heijden, 2004). However, classification of a system as "hedonic" or "utilitarian" is ultimately a function of the relative salience of its hedonic and utilitarian attributes (Chernev, 2004)—in other words, hedonism and utilitarianism are not two ends of a one-dimensional scale (Voss, Spangenberg, & Grohmann, 2003). Consequently, hedonic effects may still play a significant role in the feature acceptance of utilitarian IS features. Following van der Heijden (2004), we hence hypothesize that with regard to core IS features, PEOU exerts a positive influence on PE and that PE exerts a positive influence on ITU.

H3a: The perceived usefulness of core IS features will have a positive influence on the intention to use core IS features.

H3b: The perceived ease of use of core IS features will have a positive impact on the intention to use core IS features.

H3c: The perceived enjoyment of core IS features will have a positive impact on the intention to use core IS features.

H3d: The perceived ease of use of core IS features will have a positive impact on the perceived usefulness of core IS features.

H3e: The perceived ease of use of core IS features will have a positive impact on the perceived enjoyment of core IS features.

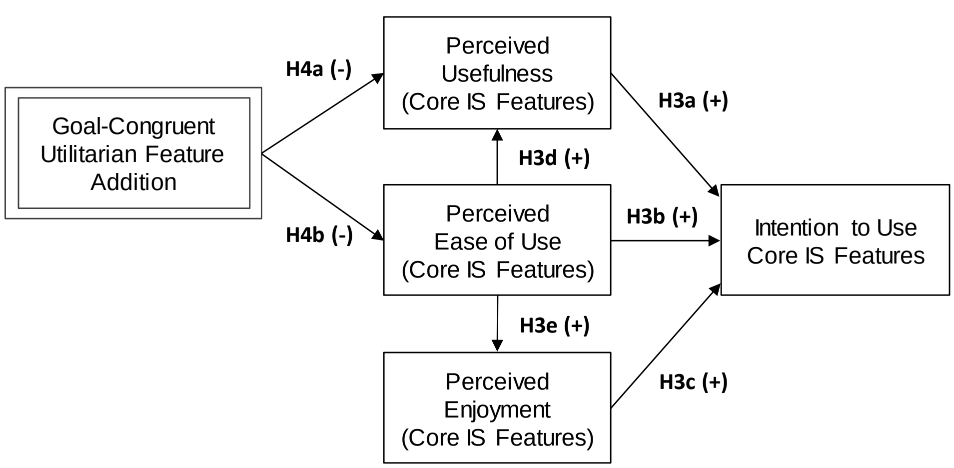

Figure 4. Explanatory Intention Model

IS features are subject to the phenomenon of subadditivity, which has a negative influence on the antecedents of usage intentions. To understand this impact, it is essential to consider the direct effect of feature additions on the user's value perception of the core features. As discussed before, in the case of feature additions, the overall value ($value_{core+addition}$) of the system is greater than the value of the original core IS ($value_{core}$) without the feature addition (cf. Equation 2). However, subadditivity implies that the resulting total value is not equal to the sum of the perceived value of both the core and the added features, as follows:

$$value_{core} + value_{addition} > value_{core+addition} \quad (2)$$

Following the argumentation of Gill (2008) and as a logical consequence of subadditivity, the individual valuations of the core and the addition suffer from the functional merger. Both sets of IS features are less valued when they are part of the same IT artifact ($value'_{core}$, $value'_{addition}$) than they would be if they were implemented separately ($value_{core}$, $value_{addition}$), as follows:

$$value_{core} > value'_{core};\ value_{addition} > value'_{addition} \quad (3)$$

with

$$value_{core+addition} = value'_{core} + value'_{addition} \quad (4)$$

Considering the goal-congruent utilitarian nature of the core and addition, we hence expect that the PU of the core IS functionality will decline as a consequence of the congruent addition. Therefore, we hypothesize the following:

H4a: Adding a goal-congruent utilitarian feature to a utilitarian IS core will have a negative effect on the perceived usefulness of core IS features.

Furthermore, we hypothesize a negative effect on PEOU as a consequence of the mental effort involved in the use of IS functionality (Heijden, 2004). Adding features increases the overall product complexity, with a potential impact on PEOU (Thompson et al., 2005). In fact, too many features can make a product overwhelming, ultimately leading to consumer dissatisfaction. The information processing theory provides a theoretical explanation for this effect. A person's ability to process information is limited because people have only a limited pool of mental resources (Lang, 2000). Thus, using added features consumes mental resources and increases the overall mental effort. Within the context of the core feature set, an overall increase in mental effort therefore entails a reduction in PEOU. Therefore, we hypothesize the following:

H4b: Adding a goal-congruent utilitarian feature to a utilitarian IS core will have a negative effect on the perceived ease of use of core IS features.

5.2 Measurement Instruments and Data Collection

With a new set of 312 MTurk participants, we repeated the same experimental procedure and design as in the second study. The participants were divided into two groups (A and B). Group A was presented with the earlier release of the app, R2, whereas Group B members were assigned to R3, which included the added weather feature. Of these participants, 68 (27.9%) were excluded from the analysis due to the incompleteness of their responses (61) or an insufficient understanding of the presented screens, as indicated by more than two wrong answers to the control questions (7). In total, 244 valid responses were collected (see Table 4 for the demographic characteristics).

This time, in contrast to the prior lab study, participants were only asked about their intention to use the core IS features. The survey questionnaire included scales for the PEOU, PU, and PE of the core features. Here, PEOU was based on three items adapted from Venkatesh & Davis (2000) and measured on a 7-point Likert scale (1 = highly disagree, 7 = highly agree). In line with the pretest, PU and PE were operationalized following Gill (2008) on the basis of Voss et al. (2003), with three items each. All items were measured using a 7-point Likert scale. The scale for measuring the intention to use core IS features was the same as in Study 2 (cf. Appendix A).

5.3 Results

We used MPlus 6.12, a covariance-based structural equation modeling tool, to test Hypotheses H3a-e and H4a-b. We first examined the measurement model to assess the reliability and validity before analyzing the structural model. Table 5 presents the results of the factor analysis. Regarding the item reliability, all indicators exhibited highly significant t-values and factor loadings of greater than 0.7 (Hair, Black, Babin, Anderson, & Tatham, 2006). One well-accepted approach to assess the quality of cross-loadings is to focus on the highest loading with a cutoff (Matsunaga, 2010). In this case, the highest factor loading of an item must be greater than an a priori determined cutoff value. A cutoff of 0.4 is commonly observed as the lowest acceptable threshold, whereas 0.7 is an upper limit. A second approach is to focus on the discrepancy between the highest and the second highest factor loadings and to ensure that the primary-secondary discrepancy is sufficiently large (0.3-0.4) (Matsunaga, 2010).

Table 4. Sample Characteristics

		Group A	Group B
Feature set		***R2***	***R3***
N		***128***	***116***
Age	Less than 25 years	34 (26.6%)	31 (26.7%)
	25-34 years	60 (46.9%)	59 (50.9%)
	35-44 years	26 (20.3%)	12 (10.3%)
	45-54 years	5 (3.9%)	12 (10.3%)
	55 years and older	3 (2.3%)	2 (1.7%)
Gen-der	Male	76 (59.4%)	66 (56.9%)
	Female	52 (40.6%)	50 (43.1%)
Monthly income	Less than $1,300	16 (12.5%)	21 (18.1%)
	$1,300-$2,600	19 (14.8%)	21 (18.1%)
	$2,600-$3,600	18 (14.1%)	10 (8.6%)
	$3,600-$5,000	9 (7.0%)	7 (6.0%)
	$5,000-$10,000	7 (5.5%)	5 (4.3%)
	More than $10,000	20 (15.6%)	23 (19.8%)
	No answer	39 (30.5%)	29 (25.0%)
Education	High school	25 (19.5%)	24 (20.7%
	Technical degree	8 (6.3%)	5 (4.3%)
	1-3 years college	44 (34.4%)	32 (27.6%)
	Bachelor’s degree	38 (29.7%)	44 (37.9%)
	Graduate degree	11 (8.6%)	11 (9.5%)
	Other	2 (1.6%)	0 (0%)
Employment status	Employed	68 (53.1%)	64 (55.2%)
	Self-employed	27 (21.1%)	18 (15.5%)
	Student (high school)	0 (0%)	0 (0%)
	Student (university)	18 (14.1%)	17 (14.7%)
	Unemployed	15 (11.7%)	15 (12.9%)
	Other	0 (0%)	2 (1.7%)
Smartphone	iPhone	54 (42.2%)	36 (31.0%)
	Samsung	39 (30.5%)	46 (39.7%)
	Nokia	1 (0.8%)	2 (1.7%)
	HTC	8 (6.3%)	6 (5.2%)
	Other	21 (16.4%)	22 (19.0%)
	No smartphone	7 (5.5%)	7 (6.0%)

Table 5. Factor Loadings

Construct	Item	PEOU	PE	PU	ITU	t-value	R^2
Perceived ease of use of core features (PEOU)	**PEOU 1**	0.936	0.264	0.476	0.407	35.423	0.877
	PEOU 2	0.867	0.245	0.441	0.377	27.360	0.752
	PEOU 3	0.917	0.259	0.467	0.399	41.866	0.841
Perceived enjoyment of core features (PE)	**PE 1**	0.220	0.781	0.112	0.340	22.534	0.610
	PE 2	0.253	0.898	0.129	0.391	34.169	0.806
	PE 3	0.234	0.831	0.119	0.362	23.882	0.690
Perceived usefulness of core features (PU)	**PU 1**	0.428	0.121	0.841	0.447	18.264	0.707
	PU 2	0.487	0.137	0.957	0.509	59.416	0.916
	PU 3	0.483	0.136	0.948	0.505	64.476	0.900
Intention to use core features (ITU)	**ITU 1**	0.372	0.372	0.455	0.855	28.253	0.730
	ITU 2	0.390	0.390	0.477	0.896	40.037	0.804
	ITU 3	**0.391**	**0.391**	**0.478**	**0.899**	**36.450**	**0.808**

Table 6. Interconstruct Correlations and Reliabilities

Measure	Cronbach's alpha	Composite reliability	PEOU	PE	PU	ITU
Perceived ease of use of core features (PEOU)	0.933	0.933	**0.823**			
Perceived enjoyment of core features (PE)	0.874	0.876	0.282	**0.702**		
Perceived usefulness of core features (PU)	0.939	0.940	0.509	0.143	**0.841**	
Intention to use core features (ITU)	0.918	0.914	0.435	0.435	0.532	**0.781**

Note: The bolded diagonal elements represent the square root of the average variance extracted (AVE)

All our primary loadings are greater than 0.7, and the primary-secondary discrepancy is greater than 0.39 for all items; thus, the quality is assured under the aforementioned criteria. The reliability of the factors was further evaluated based on Cronbach's α and composite reliability (see Table 6). All factors exceed the recommended thresholds of 0.7 for Cronbach's α (Nunnally & Bernstein, 1994) and composite reliability (Bagozzi & Yi, 1988). In addition, the average variance extracted (AVE) per factor is greater than the desired level of 0.5 for all constructs (Fornell & Larcker, 1981; Mackenzie, Podsakoff, & Podsakoff, 2011; Ping, 2004). Moreover, the value of the square root of the AVE of each factor is greater than the correlation of the factor with all other factors, demonstrating discriminant validity (Chin, 1998; Wang, Tai, & Grover, 2013). Finally, the largest correlation between any pair of factors is 0.532, which is well below the recommended upper limit of 0.7 (Mackenzie et al., 2011; Ping, 2004).

Overall fit measures were computed to test the fit of our structural model to the data. In addition to the root mean square error of approximation (RMSEA), the comparative fit index (CFI) and the Tucker-Lewis index (TLI), we used χ^2/df as an indicator of the overall fit because the χ^2 test becomes more conservative as the sample sizes increase. Following Gefen, Rigdon, & Straub (2011) and Carmines & McIver (1981), the recommended cut-off values are RMSEA < 0.1, CFI > 0.9, TLI > 0.9, and χ^2/df < 3. The results for our model exceed these recommended standards (RMSEA = 0.07, CFI = 0.96, TLI = 0.95, and χ^2/df = 2.15).

As hypothesized, significant relationships were found between the feature addition and PU (H4a) and between the feature addition and PEOU (H4b). Furthermore, the results support the hypotheses regarding the effect of PEOU on PU (H3d) and PE (H3e), in addition to supporting the effect of PU (H3a) and PE (H3c) on ITU, as expected. The model explains 42% of the variance in the intention to use the app's core features, providing evidence that the critical antecedents of this variable are covered (see Table 7).

Table 7. Path Coefficients and Explained Variance for the Structural Model

Hypothesis		Path coefficients	R2
H3a	PU → ITU	0.42*** (0.09)	
H3b	PEOU → ITU	0.13 (0.09)	
H3c	PE → ITU	0.34*** (0.07)	
H3d	PEOU → PU	0.49*** (0.08)	
H3e	PEOU → PE	0.28*** (0.07)	
H4a	i → PEOU	-0.14* (0.06)	
H4b	i → PU	-0.12* (0.06)	
	PU		0.27*** (0.08)
	PE		0.08* (0.04)
	ITU		0.42*** (0.07)
Notes: * p < 0.05, ** p < 0.01, and *** p < 0.001			

The relationship between PEOU and ITU (H3b) was only marginally significant (z = 1.72, p = 0.086). Hence, to further investigate how PU and PE mediate the relationship between PEOU and ITU, we followed Chatterjee, Moody, Lowry, Chakraborty, & Hardy (2015) and used post hoc bootstrapping to construct confidence intervals of the effects. Tests for mediation have traditionally been based on the techniques proposed by the Baron & Kenny (1986) and the Sobel (1982) tests. However, with more computing power available to researchers, the bootstrapping method has become more prevalent (Chatterjee et al., 2015; Vance, Lowry, & Eggett, 2015). Therefore, we performed multiple-mediator bootstrapping, as proposed by Preacher & Hayes (2008). The results indicate an indirect effect of PEOU on ITU through a PU of 0.20, with a 95% confidence interval ranging from 0.118 to 0.321. In addition, the indirect effect of PEOU on ITU through PE was 0.09 (95% confidence interval from 0.044 to 0.149). Finally, the direct effect of PEOU on ITU was 0.14 (95% confidence interval from 0.038 to 0.241). In summary, the results thus indicate partial mediation and, therefore, support Hypothesis H3b.

6 Discussion

The starting point of the present research was the assumption that there may be as yet unknown interdependencies between the features of an IT artifact, such that the addition, removal, or change of individual features affects the use of others. This assumption is based on marketing research findings that contradict the traditional notion that the evaluation of products by consumers follows a simple additive utility function. Rather, it could be shown that when new features are introduced, assimilation between similar features leads to a decrease in perceived marginal benefits. We proposed that these findings could be transferred to the context of IS acceptance and use and that under certain conditions, the addition of new features might have a negative effect on existing features. Whereas earlier studies have shown that system characteristics are key determinants of IS use, investigations of such more fine-grained effects with regard to usage at the level of individual features are sparse.

According to existing evidence in the marketing literature, a key antecedent for undesired assimilation effects is the goal congruence between features—that is, the features' similarity in relation to a consumer's usage goals. Furthermore, prior research points out that the phenomenon of subadditivity of utility perceptions is particularly prominent in the case of utilitarian (as opposed to hedonic) features. In the context of our empirical research, we therefore considered the example of a property insurer's mobile app, to which another feature was added that, according to app user perceptions, served goals similar to those of the existing utilitarian core features. We expected that the increased utility of the app engendered by the additional feature would also be reflected in terms of higher overall use. In contrast to this positive impact, we also expected that the use of existing core features would decline due to the goal congruence between features. To provide evidence for and to explain these effects, we conducted three consecutive studies, the results of which are summarized in Table 8.

Table 8. Overview of Study Results

Study	Purpose	Results	Limitations
Field study	Ensure external validity of the effects of goal-congruent feature additions on actual usage (H1a-b)	• H1a was confirmed: the goal-congruent feature addition exerts a positive effect on the overall IS use • H1b was confirmed: the goal-congruent feature addition exerts a negative effect on the core feature use	• No randomized field experiments • Temporal effects may apply, i.e., the treatments were released sequentially • Data were available at a device level and not at a user level
Lab Study 1	Replicate the findings from the field, under the more controlled conditions of a lab experiment	• H2a was confirmed (Group A vs. B): the goal-congruent feature addition exerts a positive effect on the overall IS intention to use • H2b was confirmed (Group C vs. D): the goal-congruent feature addition exerts a negative effect on the core intention to use	• Measurement is restricted to intention to use • Long-term use cannot be measured in a lab setting • Limited external validity
Lab Study 2	Confirm the model that explains the negative side effects (H4a-b) of the goal-congruent feature addition, in a randomized lab experiment	• H3a-e was confirmed: the same fundamental cause-effect relationships that explain system acceptance and use hold true on the level of individual features • H4a was confirmed: the goal-congruent feature addition exerts a negative effect on the perceived core usefulness • H4b was confirmed: the goal-congruent feature addition exerts a negative effect on the perceived core ease of use	• Measurement is restricted to intention to use • Long-term use cannot be measured in a lab setting • Limited external validity

In a field study, we first used a real-world data set to investigate how the addition of a new type of weather feature affects the use of the insurance app as a whole and the use of the features already available in an earlier release. Both the core features and the weather feature were perceived by users as predominantly utilitarian and goal congruent. In a simple predictive model, we hypothesized that the additional feature would increase the overall usage of the app, while the core features would be used less than they would have been used without the weather feature. Both hypotheses were confirmed on the basis of usage data collected over several months. We were thus able to show that IS users do not follow a naive "more is better" pattern in their usage behaviors but that negative influences can occur between apparently independent features. In other words, the perceived utility of an IT artifact is not equal to the sum of its parts (i.e., features), and the marginal utility of a new feature depends on the already existing features to which it is added. Although the data at this point do not allow for more precise conclusions, our observation might also be interpreted as an indication that the impact of feature addition is not limited to newly added features but influences all goal-congruent features simultaneously. Another noteworthy finding is that the observed effect seems to persist over several months and does not disappear due to increasing experience or other similar factors.

While working with field data in a naturalistic setting supported the external validity of our results, it did not afford the rigor of laboratory research. For this reason, to determine to what extent the influence of a feature addition is also reflected in the behavioral intention preceding the actual behavior, we investigated this in a second study under controlled conditions. In fact, the data showed a negative feature addition effect on the intention to use the existing core features of the mobile app. As expected, and in contrast to the negative effect, the feature addition also exerted a positive influence on the behavioral intention to use the overall app. These findings imply that in addition to the phenomenon observed in the field, there is indeed an effect on the mental decision-making process that leads to the formation of a behavioral intention. More specifically, it can be concluded (1) that usage intentions exist not only with regard to an IS as a whole but also to individual features, and (2) that adding a feature can affect these feature-related intentions. However, since the model considered in the second study was purely predictive, the results do not reveal the underlying causalities.

In the search for an explanation of the negative effect on the core feature use, we therefore tested a model based on the TAM in a further laboratory experiment. The statistical analysis showed that the presence of the weather feature in the mobile insurance app had a negative effect on the existing core features' PU and PEOU, the two classic determinants of usage intentions. The first effect, in particular, is interesting, as it highlights the role of congruent usage goals. If only the impact on PEOU was negative, the reduced usage intention could have been explained by the higher complexity of the overall system, as a larger number of features generally makes an IT artifact more complex for the user. However, this monocausal explanation is contradicted by the observation that PU was also negatively influenced. The latter finding supports our assumption that the newly added function might be perceived as goal congruent and that the core features were therefore considered less useful. The other TAM-related hypotheses were confirmed and provide evidence for the causal chain from feature addition to behavioral intention. In addition to the significance of the individual effects, the model also has a good model fit and explanatory power with regard to the ITU variable. Therefore, it can be concluded that the mental process for deciding to use individual features of an IT artifact basically follows the same rationale as that at the system level. Taken together, the results indicate that usage decisions are made by IS users in a way similar to that of consumer purchasing decisions examined in marketing research, which would imply that the decision for or against the use of an IT artifact may be interpreted as a function of several individual feature-related evaluations.

6.1 Theoretical Implications

The results of our research have various implications for established theories in the area of IS acceptance and use. The most obvious implication is related to the dependent variable—that is, the IS use construct. In the present literature, IS use has been conceptualized and operationalized in various ways; for example, in terms of use duration, frequency, or intensity (Venkatesh, Brown, Maruping, & Bala, 2008). In almost all cases, however, the construct refers to the use of an entire system and not to smaller functional units of the same. In contrast, we argue that IS use can also be understood and investigated as the use of individual features. In doing so, we are following various calls for finer-grained studies of IS acceptance and use to uncover the phenomena that would otherwise go unnoticed (Benlian, 2015; Burton-Jones & Straub, 2006; Venkatesh et al., 2012). Our results indicate that there may be dependencies between the acceptance and use of individual features as well as between features and the overall system. In our statistical analyses, we have shown that such effects, which may not be predicted or explained by using established models, occur both in the field and in the laboratory. In summary, for future theory development, it follows that the IS use construct and the corresponding measurement instruments, currently still limited to system use, should be further extended to the use of individual IS features.

A second implication refers to the models and independent variables that are assumed to explain the feature acceptance and use. The established theories attribute IS use to various influencing factors which, similar to the dependent variable, almost always refer to the IT artifact as a whole. With the shift of the focus to the feature level, the issue arises regarding whether these known influencing factors can be transferred to the feature level and to what extent further determinants must be included in the resulting models. A subsequent challenge may then be seen in the integration of the existing models of system usage with models of feature usage. Our results suggest that essential elements of the TAM model may be applicable to the acceptance and use of IS features. The similarity between explanatory models at the system and feature levels may thus provide a future starting point for formulating a theory of IS acceptance and use that combines both perspectives. However, in contrast to total system use, feature acceptance and use may occur in the form of several simultaneous processes that influence each other. Within the scope of our study, we were able to provide evidence for such an influence in the form of assimilation between features. The formation of an intention for IS use could hence be interpreted as the sum of various feature-related mental decision processes, which entails additional complexity.

Finally, conclusions can also be drawn from our research regarding the role of usage goals in models of IS acceptance and use. The effect we investigated in the context of feature additions was essentially based on the congruence between the usage goals underlying different features. However, it is interesting to note that established models from the IS literature do not explicitly consider the influence of usage goals in the formation of usage intentions. One possible reason for this may be that the theoretical roots of TAM, UTAUT, and their extensions go back to classic models from psychology research, which did not yet incorporate the concept of behavioral goals. In contrast, more recent research indicates that goal-related factors (e.g., goal desire, goal intention) are essential determinants of behavioral intentions (Bagozzi 2007; Loock, Thiesse, & Staake 2013). The present research provides an example that highlights the possible relationships between usage goals and the use of information systems. Regardless of whether IS usage is considered at the system or feature level, to describe IS use as a form of goal-directed behavior, the corresponding theoretical models should therefore be extended to include the abovementioned insights from newer psychology research.

6.2 Implications for Practice

The practical implications of our research are of fundamental importance for all developers and operators of information systems intended for end users. This is especially true when design, implementation, and continuous improvement of systems follow a feature-oriented approach. The latter applies to nearly all modern methods of software engineering, such as Scrum or Extreme Programming, which, in contrast to the traditional waterfall model (Benington, 1983), no longer provide a coherent design phase in which the specification of the system to be created is elaborated as a whole. Rather, agile models comprise numerous smaller development cycles based on feature lists, which are constantly updated and reprioritized from one iteration to the next (Dybå & Dingsøyr, 2008). As a result, project teams must decide frequently and at short intervals the features that are to be implemented in the next step. However, support from agile methods on this issue is usually limited to the general advice to prioritize features based on the business value created (Daneva et al., 2013).

Against this backdrop, the results of our research should be understood as a recommendation that the value of new features should never be evaluated separately but always in the context of the system in which they are to be integrated. If this evaluation does not happen, there is a risk that the increase in benefit will be misjudged regarding the perception of future users. In our studies, we could show such an effect for the case of utilitarian, goal-congruent features. However, the marketing literature suggests that such interdependencies may also exist between other types of IS features. To optimally manage the development process, it is hence necessary to precisely understand the perceived characteristics of features and the possible negative effects between them.

These implications are particularly relevant for companies whose revenues, cost savings, or other benefits depend only on a subset of the digital services they make available to their customers. For example, many financial service providers on the Internet not only allow for conducting transactions on their platforms but also offer users real-time market information, data analysis tools, discussion forums, and other complementary functions, free of charge. The underlying hope is that the variety of functions will attract a large user base, thereby creating strong customer loyalty through network effects and switching costs, which ultimately leads to a higher number of transactions. The same strategy applies to web portals and mobile apps based on the so-called “freemium” revenue models (Kumar, 2014), in which only part of the entire functionality is monetized. In all these cases, companies face the challenge of making their IT-based services as rich and attractive as possible without negatively affecting the core features that form the basis of their business model.

For the near future, it is foreseeable that with the rise of the Internet of Things and the proliferation of “smart connected products” (Porter & Heppelmann, 2014), the issues described will also become relevant for numerous manufacturing companies beyond the IT industry. Unlike conventional physical goods, the visible form and function of smart products are complemented by data and services from the cloud. In many cases, such products connected to the Internet serve as platforms on which recurring revenues result not only from product sales but also from the use of various digital services (Hui, 2014). In these cases, too, companies must be prepared for the implementation of new features to conflict with existing revenue-generating features. A possible solution in such cases could be, for example, to not add additional features to the smart product free of charge but to offer them as separate add-ons.

6.3 Future Research Perspectives

Our results offer opportunities for further research in various directions. One limitation (among others) of the present study is its focus on goal-congruent feature additions to a utilitarian IS core. This focus was chosen because prior studies indicate that the subadditivity effects of goal-congruent feature additions associated with utilitarian features are stronger than they are for hedonic features. However, subadditivity likely also occurs in the latter case scenario, although this remains to be confirmed empirically in an IS context. Future research could take advantage of this gap and examine subadditivity using a hedonic setup. Such research should investigate perceived enjoyment rather than perceived usefulness, because existing theory suggests that feature addition is associated with both a decrease in perceived feature enjoyment and an increase in overall perceived system enjoyment.

Another avenue for further work would be to extend the proposed explanatory model. We were able to confirm the impact of feature addition by means of the predictive models in Study 1 and 2. Since the field study not only measured usage intentions but also actual use, we are rather confident that these results would be confirmed in further studies. Study 3 on the explanatory model, however, was limited to the intention to use as the dependent variable. Therefore, future research should consider a possible intention-behavior gap. Although use intentions have been demonstrated to be strong predictors of actual use in numerous studies, it is also known that other factors such as habits may prevent people from turning their intentions into actions (Venkatesh et al., 2012). As our study did not consider long-term usage data, it can be assumed that habits play a minor role. In other cases, however, the influence of new features might be mitigated by the habits of existing users.

Furthermore, we propose that future research should look more closely at the intention-forming process based on actual usage. Since our second lab study was not based on actual app usage, subjects might also assess perceived usefulness, perceived enjoyment, and ease of use differently in the case of actual usage. Specifically, the latter construct (PEOU) might be assessed differently in the case of real usage. Interacting with the actual app and gradually exploring it in an active and self-determined way, rather than consuming screenshots in a predefined order, might be a more effective way of becoming familiar with the app (Benyon, 2014), particularly if the app is more complex, as is the case in the feature-addition scenario. As a result, the difference of ease of use between the two experimental conditions (app with and without feature addition) might decrease. Consequently, the negative effects of feature addition might rely less on complexity effects and more on assimilation effects. Furthermore, the impact of feature changes on factors beyond PU, PEOU, and PE remains an unresolved research issue. In this context, the extent to which insights from the system level are transferrable to finer levels of granularity, such as feature sets or individual features, is yet to be determined.

Finally, we see several opportunities for conducting studies regarding the interface between behavioral IS research and design research. Theory-driven empirical research on IS features may be in a better position to be combined with design-oriented studies than system-level approaches are since features are at the center of many IS development methods. Feature-level studies may thus be able to generate novel insights of immediate relevance to the IS design and implementation process and vice versa.

7 Conclusion

As can be observed in practice in almost all forms of IT, both individual features and their combination within an IT artifact can change significantly over time. From a scientific point of view, this raises various questions regarding the effects of such feature changes on IS acceptance and use. On the one hand, it can be assumed that, for example, the addition or omission of features will affect the use of the artifact as a whole in one way or another. On the other hand, it could also be assumed that there are interactions between individual features so that changes to one feature will have positive or negative effects on the acceptance and use of other features. The present study was able to show that such effects actually occur in connection with the congruence of usage goals. More specifically, this study revealed that these interaction effects can be negative with regard to core IS feature acceptance and use. Thus, adding a goal-congruent feature might harm existing features, an insight which must be considered when deciding to implement new features. To discover and explain effects that have not yet been adequately covered by the existing models, the results indicate that future research should take the use of individual features into greater account. Our research hence offers only a first step toward a more comprehensive understanding of IS acceptance and use at the level of individual features.

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Appendix A: Measurement Instrument

Table A1. Construct Measures Pretest

Construct	Items	References
Perceived usefulness of app's base (weather) features	Overall, I find the base (weather) features…	Voss et al., 2003
	… unhelpful—helpful	
	… impractical—practical	
	… not functional—functional	
Perceived enjoyment of app's base (weather) features	Overall, I think the base (weather) features are…	Voss et al., 2003
	... dull—exciting	
	… not thrilling—thrilling	
	… disgusting—enjoyable	
Goal congruence	How similar is the goal associated with base features and weather features?	Gill, 2008; Martin & Stewart, 2001
	How similar is the reason for using base features and weather features?	

Table A2. Construct Measures Lab Study 1

Construct	Items	References
Intention to use app	I would use the presented app frequently	Venkatesh et al., 2012
	I would use the presented app regularly in my daily life	
	I would use the presented app often	
Intention to use app's base features	I would feel comfortable using the presented base features	Davis et al., 1989; Liu et al., 2004; Nicolaou & McKnight, 2006
	I would use the presented base features	
	I would recommend use of the presented base features to other colleagues	

Table A3. Construct Measures Lab Study 2

Construct	Items	References
Intention to use app	I would use the presented app frequently	Venkatesh et al., 2012
	I would use the presented app regularly in my daily life	
	I would use the presented app often	
Intention to use app's base features	I would feel comfortable using the presented base features	Davis et al., 1989; Liu et al., 2004; Nicolaou & McKnight, 2006
	I would use the presented base features	
	I would recommend use of the presented base features to other colleagues	
Perceived ease of use of app's base features	Interaction with the base features does not require a lot of mental effort	Venkatesh & Davis, 2000
	I find the base features easy to use	
	The interaction with the base features is clear and understandable	
Perceived enjoyment of app's base features	Overall, I think the base features are…	Voss et al., 2003
	... dull—exciting	
	… not thrilling—thrilling	
	… disgusting—enjoyable	
Perceived usefulness of app's base features	Overall, I find the base features…	Voss et al., 2003
	… unhelpful—helpful	
	… impractical—practical	
	… not functional—functional	

Appendix B: Mobile Insurance App

B1. Exemplary Screenshots of Core Features

Figure B1. My Agency

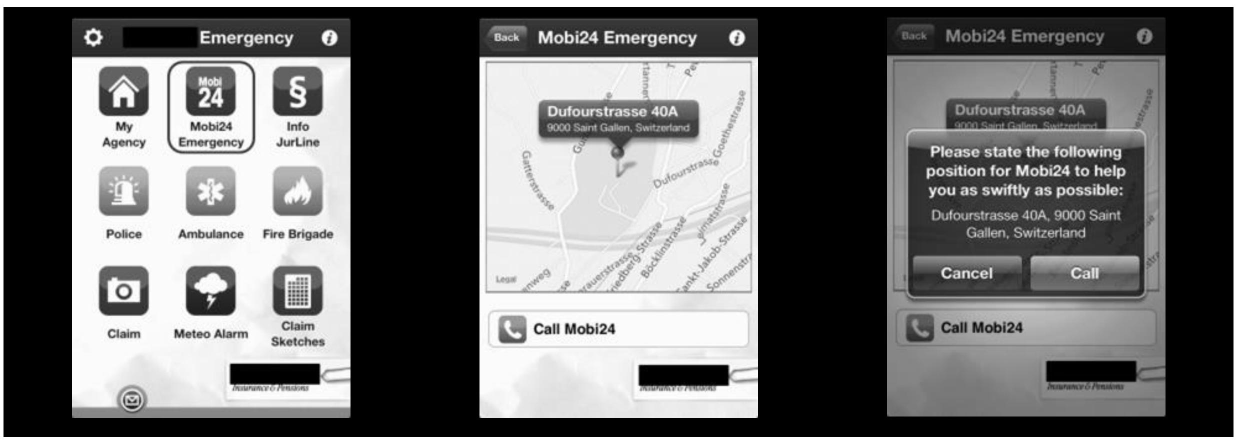

Figure B2. Insurance Emergency Call

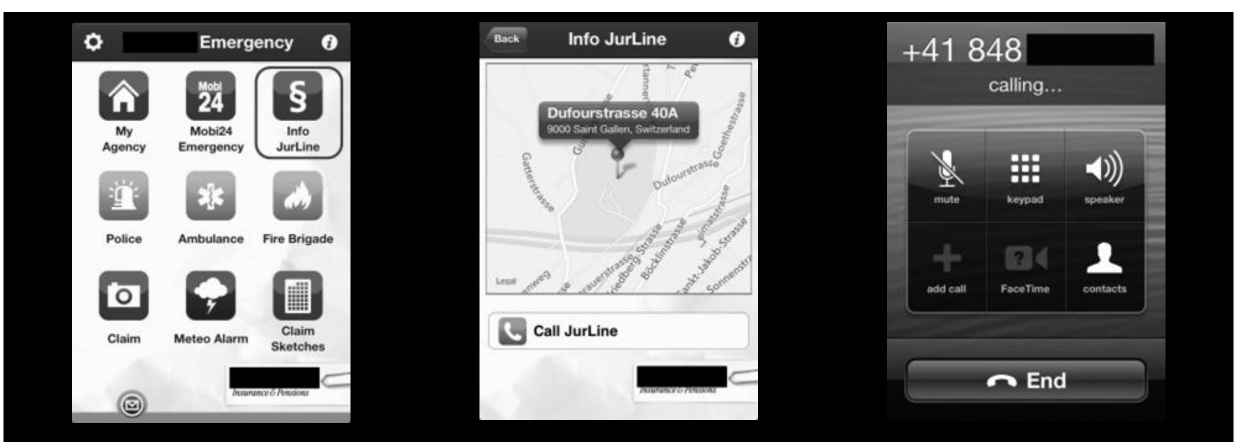

Figure B3. Insurance Legal Help Call

Figure B4. Public Emergency Call

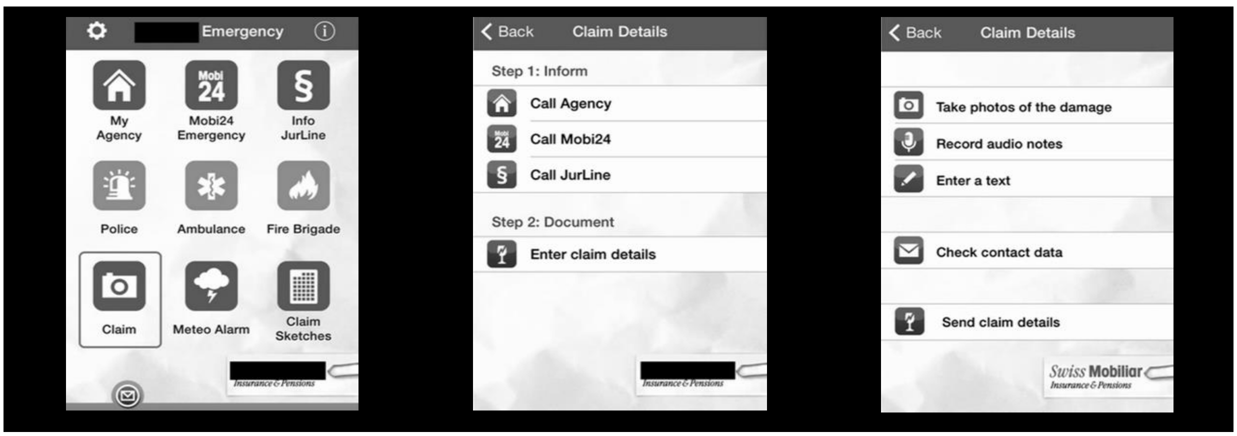

Figure B5. Claim Management

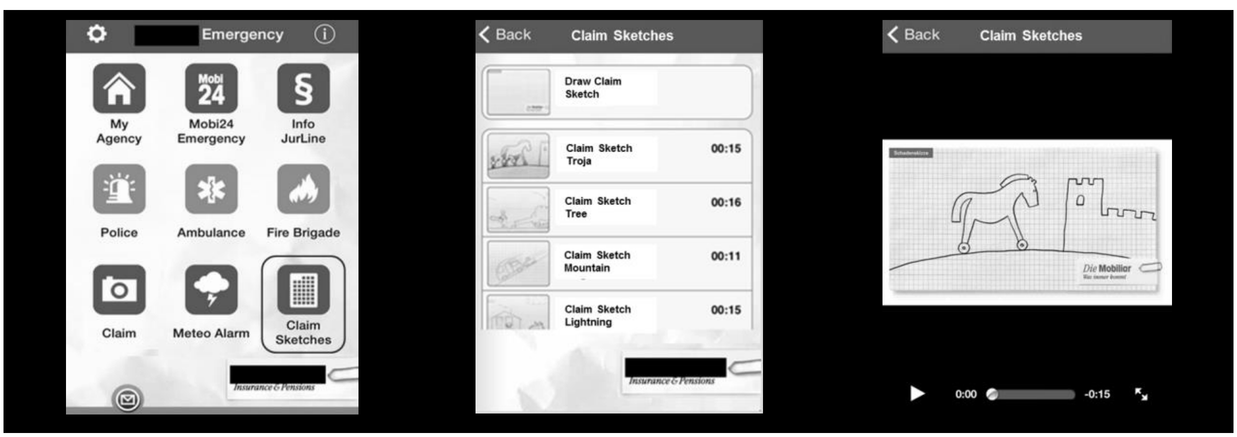

Figure B6. Claim Sketches

B2. Exemplary Screenshots of Additional Features

Figure B7. Meteorology Alarm

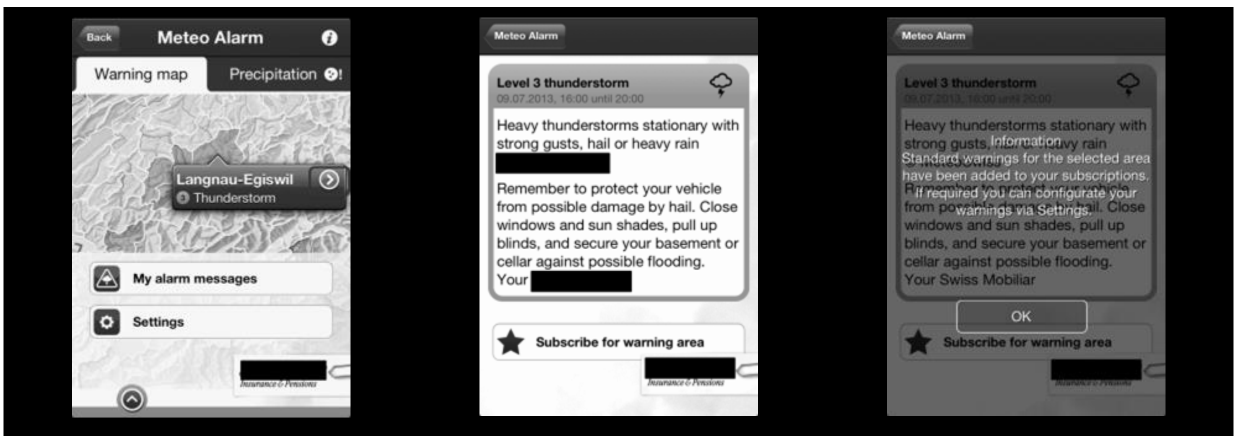

Figure B8. Warning Details

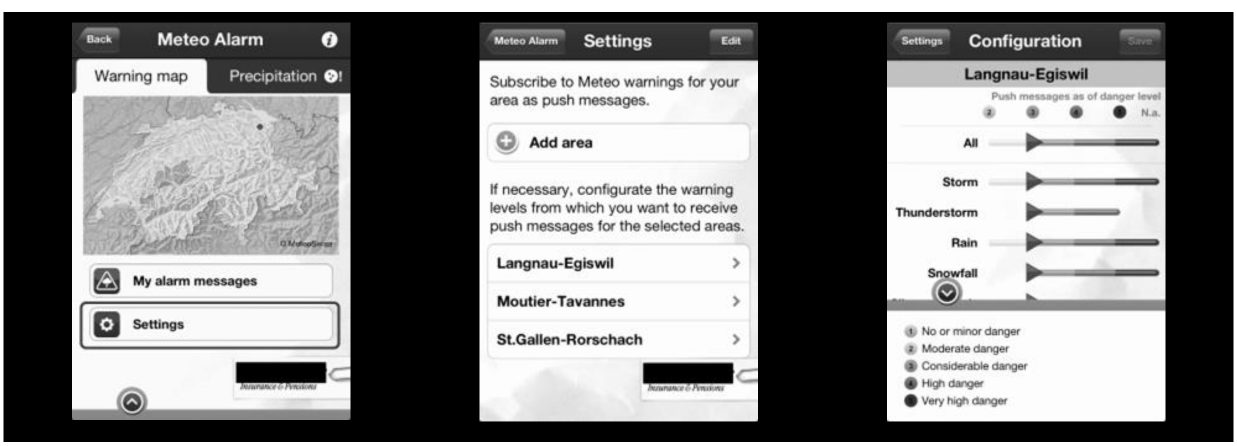

Figure B9. Warning Settings

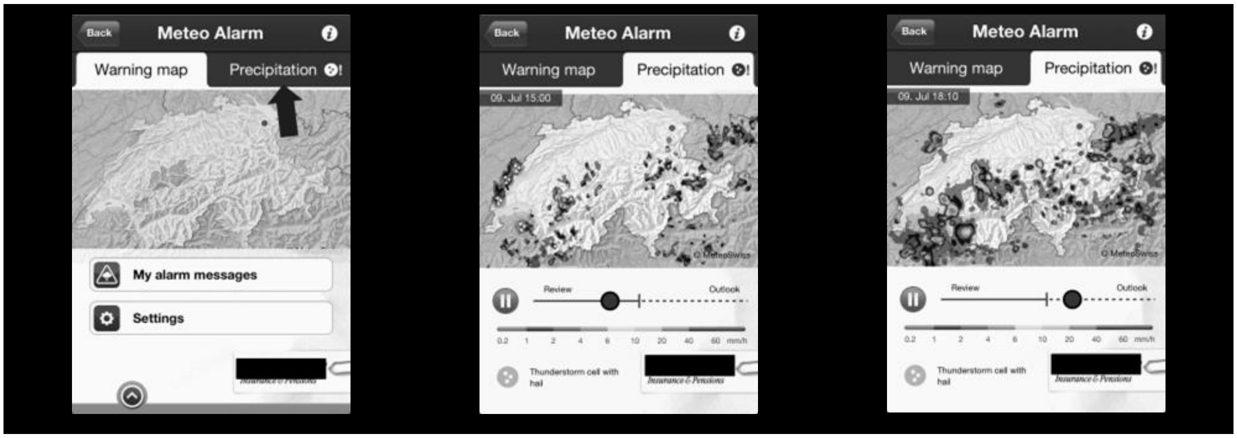

Figure B10. Weather Forecast

Appendix C: Utilization of MTurk

Table C1. Participant Recruitment, Survey Procedure, and Data Cleaning (Based on Steelman et al. 2014)

Criteria	Characteristics
1. Participant demographics	• We followed Steelmann et al. (2014) in their assessment that the use of platforms such as MTurk should be limited to the US and restricted the MTurk settings accordingly. H1b was confirmed: the goal-congruent feature addition exerts a negative effect on the core feature use. • Table 3 (predictive intention model) and Table 4 (explanatory intention model) provide the demographics of the corresponding MTurk samples, including information on age, gender, income, education, and employment.
2. Participation restrictions	• Location: we determined that the participants must be located in the US. • Computer system requirements: we did not enforce specific restrictions. MTurk and the applied survey platform require a standard web browser. • Survey experience: survey experience was a participation requirement.
3. Payment incentives	• The participants received a small monetary compensation. • An additional bonus was not offered.
4. Task timeline	• The maximum time for completion was set at 20 minutes to foster processing without major interruptions. • The average time to task completion was 5.1 (core condition) resp. 7.9 (core + weather condition) minutes for the predictive intention model (Section 4). • The average time to task completion was 5.9 (core condition) resp. 8.5 (core + weather condition) minutes for the explanatory intention model (Section 5).
5. Data quality questions and checks	• To assure an adequate understanding of both the app and the requested assessments, we included additional comprehension checks in the survey to validate that the participants had viewed and understood the screens and explanations. • The comprehension checks were short and simple multiple-choice questions. Depending on the experimental condition, 8 (core) resp. 16 (core + weather) statements about the app had to be classified as true or false. • To avoid trial-and-error behavior, we did not inform the participants about the correctness of their answers during the questionnaire.
6. Detailed data cleaning procedures	• We excluded participants if their answers were incomplete or if they did not have a sufficient understanding of the screens, indicated by more than two wrong answers to the control questions (see Sections 4.2 and 5.2 for specific details). • To ensure that subjects did not participate in the subsequent experiments, we highlighted that repeated participation would not be compensated and checked anonymous worker IDs for repeated participation.

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